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On the concept of a supervisory, fuzzy set logic based, advanced filtration control in membrane bioreactors

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ABSTRACT

The filtration process within a membrane bioreactor (MBR) is mostly controlled in a classic way through typical set-points such as aeration flow rate, filtration duration, backwash frequency or relaxation duration. The values of these filtration set-points result from "experience" and remain often unchanged during the installation's operational lifetime. Filtration is dictated considerably by membrane fouling phenomena. The fouling potential of the mixed liquor however can significantly fluctuate, even daily, from changing influent characteristics. Fixed set-point values thus may represent sub-optimal filtration conditions. Consequently, a supervising advanced control system, being able to continuously adapt the set-point's values would be beneficial regarding the MBR filtration process optimization. Such optimization could reduce the corresponding MBR energy consumption, e.g. linked to the filtration related membrane aeration. An Advanced Control System (ACS) based on Fuzzy Set Logic (FSL) is introduced here, enabling to supervise an existing classic membrane filtration control system. Such ACS is able to daily (or even more frequent) optimize the set-points of the underlying classic control system, from the input of various sensor and process parameter values. The theoretical background and practical implementation of the FSL based ACS concept is explained.

Keywords: Bioreactor, Membrane, Fouling, Fuzzy, Advanced, Control, Optimization

1. Introduction

Set-points of the MBR filtration process control include e.g. aeration, backwash, filtration interval and relaxation interval. Those are mostly deduced from the experience of the MBR membrane module producer and/or MBR operator. These set-points are related to counter-acting membrane fouling phenomena since fouling can reduce the permeate flux significantly. Multiple membrane fouling phenomena exist and are in general extremely complex [1], since they are linked to particle fouling, molecular adhesion, biofouling and scaling. A universal mathematical fouling model which accurately describes the outcome of all these complex phenomena, acting moreover simultaneously, does not exist. In particular, it would take a wide range of sophisticated and expensive on-line devices to measure the fouling determining parameters (e.g. particle size distribution of particle foulants, zeta-potential, chemical analyses, etc.). From an economical point of view, the implementation of such

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high-tech devices obviously would also be prohibitive. This would require the build of a control system, being based on a predictive model and multiple expensive (on-line) characterization instruments.

The pressure driven membrane filtration process in a MBR in fact cannot be adequately mathematically modeled. It is not possible to implement model equations in the filtration control system. However, Fuzzy Set Logic is a well known and adequate approach in those cases that the human knowledge of a process is "vague". The term "Fuzzy Logic" is not used here since such description evokes in some people's minds the wrong perception of "logic" that would be "fuzzy". The description "fuzzy set logic" (FSL) is therefore more appropriate since FSL in fact handles fuzzy sets in a logical way. FSL is nowadays implemented in many process controls within different industrial and civil domains, including automotive, chemical, metallurgical, food, photographical and video recording, image analysis, medical, etc. applications [2–7]. It is however novel in the MBR membrane filtration control, as described in this publication.

A FSL control system uses multiple FSL control blocks. Each block handles one particular set-point of the supervised (existing) classic control system. Such configuration resembles in some extent to the approach of a human operator who would manually fine-tune each set-point from experience/knowledge. The FSL based ACS, as described in this publication, completely maintains the existing filtration control system within an MBR installation, in whatever form (PLC, PC control based, etc.). The higher level ACS thus only supervises the set-points related to e.g. the duration of the relaxation, the flow of coarse bubble aeration of the membrane module or the flux of backwash cleaning. It does however not interfere further with the internal actions of the existing "lower" level control system.

The objective of this publication is to briefly introduce FSL principles, to demonstrate the feasibility of the implementation of a FSL based, set-point supervising, ACS on top of a classic filtration control system and to show some practical results of a working ACS.

2. Methods

2.1. *Fuzzy sets and fuzzy control principles in brief*

The first publication [2] by Prof. Lotfi Zadeh ("Systems Theory" at the University of California, Berkeley) on FSL appeared in 1965. The concept of fuzzy sets are demonstrated here very briefly through an arbitrary example of temperature sets, while comparing crisp sets and fuzzy sets (the description "crisp" is used in FSL literature). Within Fig. 1 and Fig. 2 the example is restricted to only three sets A, B and C. Sets can be considered as distribution functions, while giving the frequency of occurrence of a specific temperature.

Non-fuzzy "crisp" control systems use sets as shown in Fig 1. In the crisp set A "Temperature too low" of Fig. 1, all temperature frequency of occurrence values are equal to 1 for temperatures below 20°C and equal to 0 for temperatures above 20°C. The complete crisp set A ("crisp" since a step function) is also called a "membership" function showing "membership values". The crisp set C is also a step function and analogous to crisp set A while having a step at 25°C and reflecting a "temperature too high" membership. The crisp set B is somewhat more complex since there are now two steps involved: the temperature values between 20°C and 25°C have now a membership value of 1 ; the temperature values at the left from 20°C and at the right from 25°C have a membership value of 0.

In fuzzy control systems very special sets are used. As in the crisp set A of Fig. 1, all temperature values within the fuzzy set A of Fig. 2 also belong to the distribution curve called "Temperature too low". But now, the fuzzy set aspect is introduced. In the fuzzy set A all values below 17.5°C have the membership value of 1 while all temperature values above 22.5°C have the membership value of 0. The temperature values within the interval 17.5°C–22.5°C then have no longer a crisp value of either 0 or 1 but a value between 0 and 1.

This is also the case in the fuzzy set B within the interval 17.5°C–22.5°C. It is observed that set A and Set B are overlapping. As a result, for a specific temperature value : in the overlapping interval 17.5°C–22.5°C of the fuzzy sets A and B, the sum of the membership values is

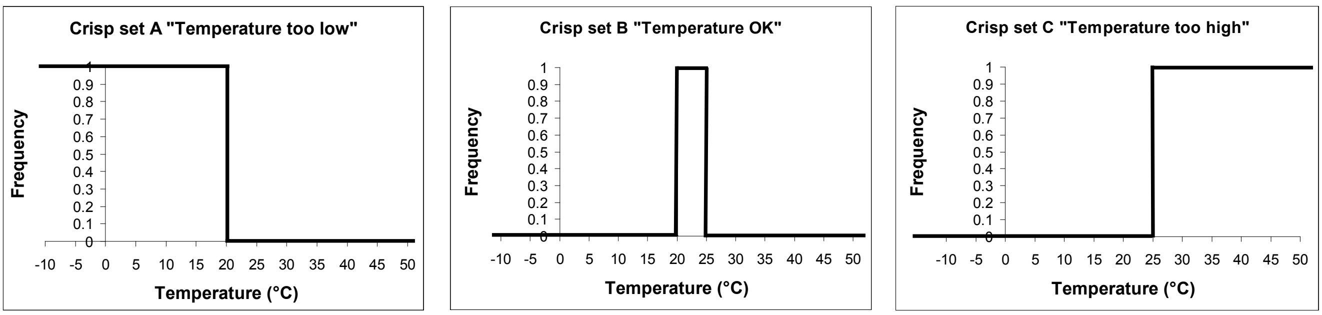

Fig. 1. Arbitrary example of crisp sets.

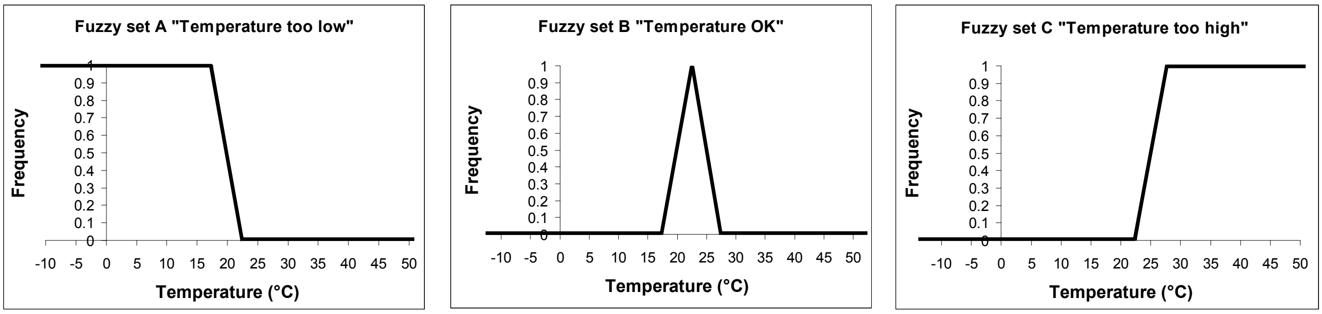

Fig. 2. Arbitrary example of fuzzy sets.

equal to 1. In an analogous way the fuzzy sets B and C are also overlapping, but in the interval 22.5°C–27.5°C. One particular temperature value therefore can belong simultaneously to two, or even more, different membership functions. This is the reason that the description "fuzzy" emerged.

This approach corresponds in some extent to different human's "vague" or "fuzzy" opinions. The fuzzy set approach therefore allows to mimic in a mathematical way the non-crisp judgment, but however very successful control approach of humans. The cybernetic abilities of the human brain to control very complicated processes are indeed remarkable.

In a FSL based control block (Fig. 3, discussed in more detail in section 2.2) there are four basic modules: a fuzzification module, a logical inference module, a fuzzy rules module and a defuzzification module. The fuzzification module enables to process the incoming crisp sensor values into fuzzy set values. These are then processed by the fuzzy knowledge modules which consist of the logical inference and the fuzzy rules module. The fuzzy results then need to be defuzzified into crisp values which are send as new set-point values to the underlying existing/classic control system.

2.2. Advanced MBR filtration control system

An existing MBR filtration control system is typically based on a PLC configured control. It is standard practice to define specific values ("set-points") of the different filtration operational parameters. In most cases, the set-point values are determined from "human operator experience" (MBR system builder's or MBR operator's experience). The set-points are often fixed at the operational start of a new MBR installation. During further operation of the installation, the set points remain often unchanged or are either only adapted by a human operator in a minor way. This evidently increases the risk of having an underperforming MBR, e.g. in the case of an excessive membrane aeration despite an actual low MBR's mixed liquor fouling propensity. It is obvious that a continuous and automatic fine-tuning of the filtration parameters within the basic level control system could enhance the MBR filtration performance. This is possible through an ACS, on top of the hierarchical "lower level" control system (Fig. 3).

A FSL based ACS was developed by first defining all possible set-points within the membrane filtration control of the MBR (it should be remarked here that this paper does not consider the control of the sludge aeration process which is related to the oxidation of the sludge and is not part of the membrane filtration process). The membrane filtration process set-points can be considered as output variables of the ACS. They can be linked to actions involving the removal of reversible foulants by "mechanical" actions such as backwashing, back pulsing, aeration and relaxation. In addition, the dosing of floc modifying or coagulating agents can be considered since such additives can prevent fouling. Finally, membrane maintenance cleaning related set-points (thus not the typical yearly intensive cleaning) can also be implemented in the ACS. A total of 17 set-points could be defined in this way as indicated in Table 1.

With respect to the input variables (sensor data), the membrane fouling propensity of the MBR mixed liquor

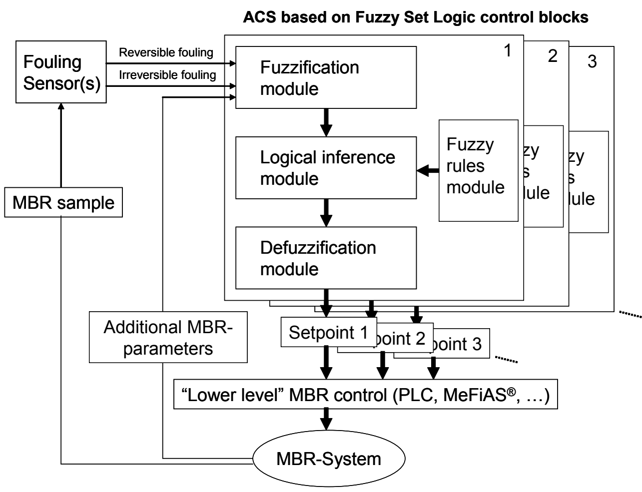

Fig. 3. Advanced control system based on FSL.

Table 1
ACS related set-points

Output variable set point	Output variable (ACS generated set point)		Fouling class
1	Backwash	Flux	Reversible
2		Duration	Reversible
3		Interval	Reversible
4	Back pulse	Amplitude	Reversible
5		Duration	Reversible
6		Interval	Reversible
7	Aeration	Flow	Reversible
8		Duration	Reversible
9		Interval	Reversible
10	Relaxation	Duration	Reversible
11		Interval	Reversible
12	Floc modifying agent (preventive)	Dose	Reversible (/irreversible)
13		Frequency	Reversible (/irreversible)
14	Chemical cleaning (maintenance clean)	Dose	Irreversible
15		Frequency	Irreversible
16	Coagulant (preventive)	Dose	Irreversible/(reversible)
17		Dosing frequency	Irreversible/(reversible)

is evidently the prime sensor information for an ACS. From the theoretical complexity of fouling phenomena, the direct measurement of the fouling propensity of a feed is a valuable approach. VITO thus developed a pragmatic fouling measurement method which enables to measure both the reversible and irreversible fouling propensity of an MBR sludge. The VFM originally was based on a dead-end filtration mode, as described in [8–10]. Within the AMEDEUS project (http://www.mbr-network.eu/index.php), the dead-end based VFM was extended into a cross-flow based MBR-VFM, while using a tubular membrane and a controlled aeration [11,12]. The MBR–VFM is based on a single tubular membrane in which an air-lift effect is created, in a controlled way, by applying defined Taylor air slugs. As a result, a first filtration curve can be obtained while applying a standardized filtration protocol (at a specific trans-membrane pressure and a low air lift flow, thus low turbulence mode) on the MBR mixed liquor. From this first filtration curve the reversible fouling fingerprint of the MBR mixed liquor is extracted and converted into a standardized MBR–VFM reversible fouling propensity curve. The succeeding filtration cycles in the MBR–VFM apparatus are then performed at a higher (standardized) aeration rate in order to promote irreversible fouling (from the higher turbulence and thus higher flux). From these additional filtration curves, which show a decline in membrane permeability, the irreversible fouling propensity can be extracted.

The MBR–VFM thus allows graphical representation in a standardized, filtration relevant way, of the reversible and irreversible fouling propensity by plotting V/A (permeate volume per m² of membrane) against $R_{tot,rev}/R_m$ or $R_{tot,irrev}/R_m$ (ratio of total hydraulic reversible or irreversible resistance versus membrane resistance). This approach preserves all measured fouling data and corresponds therefore to a multiple value fouling characterization method (in contrast with the single point fouling measurement techniques). Both MBR–VFM finger-print graphs are used as the primary sensor input for the advanced control system (ACS). It should be noted that, with respect to the automatic interpretation of both MBR-VFM fouling fingerprints, a fuzzy set logic (FSL) based image recognition system was also implemented, as illustrated in Fig. 4. Details on the MBR–VFM graphs fuzzy image recognition system will be the subject of an additional specific publication.

The ACS receives from the MBR–VFM apparatus crisp values F_{rev} and F_{irr} which are standardized in the interval 0–100 (%, low to high fouling). Next to the primary fouling sensor input values from the MBR–VFM, additional process parameters can be used as input variables to the ACS. Such input parameters may include temperature, pH, mixed liquor suspended solids (MLSS), solids retention time (SRT), etc. In Fig. 5, the FSL based ACS main dialog window is shown, including the set-points and the input process parameters. The software handles the input parameter values as percentages (0–100%) within a user specified interval; e.g. the MBR temperature is between min 5°C (0%) and max 30°C (100%) over a one year's period. Such standardization simplifies in an important way the definition and handling of the fuzzy sets within the fuzzification modules.

Each set-point as represented in Fig. 3 has an individual FSL control block (which also can be activated or

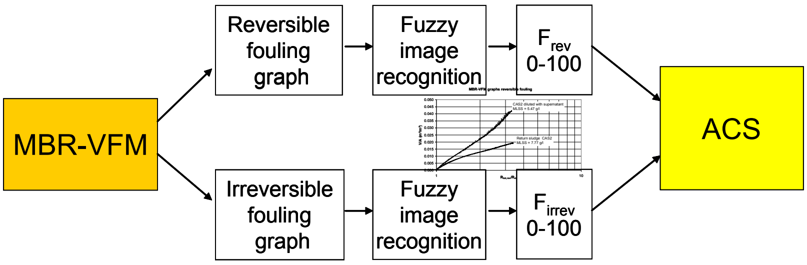

Fig. 4. Conversion of MBR–VFM fouling graphs through FSL based image recognition software.

de-activated by a MBR operator). The crisp output value (a set-point value) of each FSL control block is also situated in a standardized range of 0–100% as to simplify the fuzzy set handling in the FSL control blocks. A range of 0–100% for a specific set-point is then also corresponding to that set-point's minimum and maximum technical value. E.g. the set-point AirFlow of the membrane module aeration is defined in the range of a min value of "x_{min}" m³/h (corresponding to 0%) and a max value of "x_{max}" m³/h (corresponding to 100%). After defuzzification, the ACS thus first produces a crisp set-point value between 0 and 100%. That value is then recalculated as the corresponding value in the range "x_{min}–x_{max}" and passed as the new set-point value to the "lower level" control system.

The 0–100 % range normalization of both input and output parameters introduces "general applicable" and "implementation friendly" ACS features. The tuning of the ACS thus becomes more transparent. The ACS can be considered as a supervising system which is able to control, "in parallel", multiple set-point values. Human expert operator knowledge is implemented in the fuzzy rules modules within the multiple FSL control blocks and executed.

2.3. Implementation of the ACS

At VITO, MeFiAS® software was originally already developed under LabVIEW for the full control of any pressure driven membrane filtration system (MF, UF, NF, RO) [13]. The set-point values within this basic control software need to be set manually by the operator from her/his heuristic filtration process operational knowledge. Such MeFiAS® software was thus adapted to the MBR filtration process control. It allows an automatic filtration parameter data acquisition and total control of the filtration process (even through a remote phone or internet connection).

The FSL based ACS was then developed within LabVIEW's Fuzzy Toolbox [14]. Evidently the existence of such a dedicated Toolbox within the LabVIEW environment was a large advantage regarding the integration and linking of the ACS to the MeFiAS® software.

As an example, a typical FSL related screen print from the Fuzzy Toolbox is illustrated in Fig. 6, showing the fuzzy sets as introduced for the input parameter "Temperature" (upper) and the output (lower). As another example, Fig. 7 shows the typical fuzzy sets as used for the output parameter AirFlow (aeration), including the

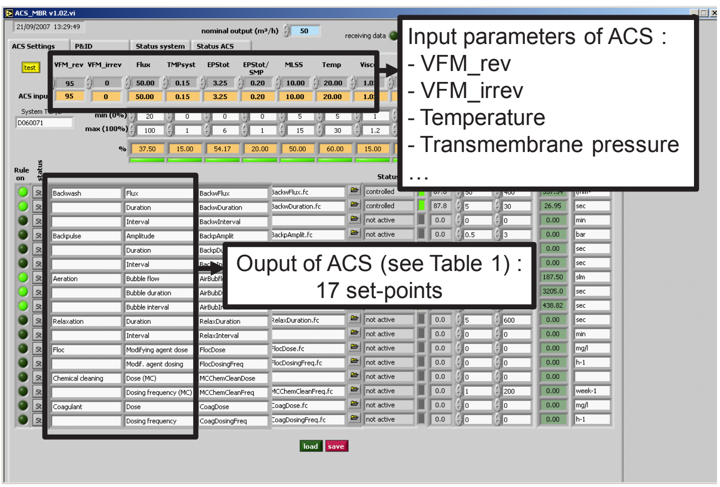

Fig. 5. ACS basic dialog window for the selection of ACS input (horizontal top) and output (vertical left) parameters.

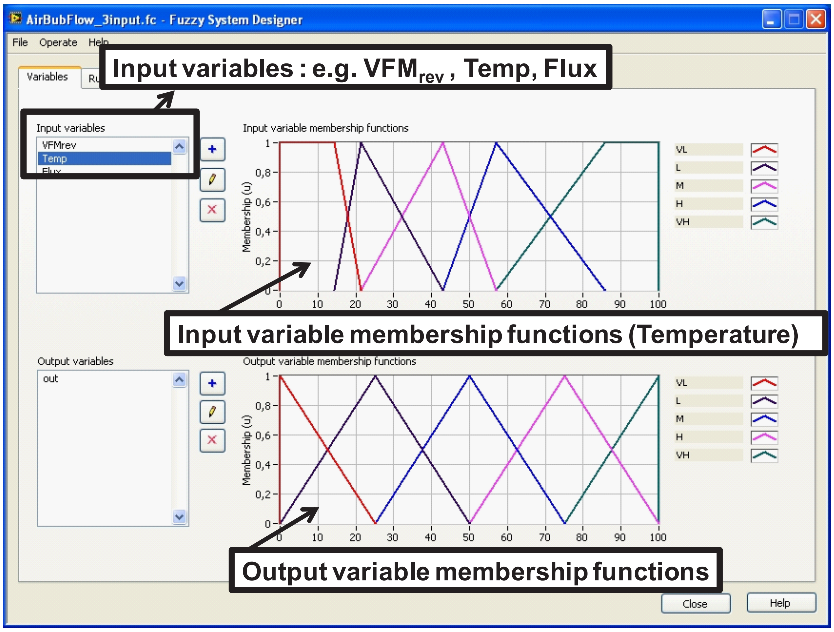

Fig. 6. Fuzzy sets for the input variable "Temperature" and output.

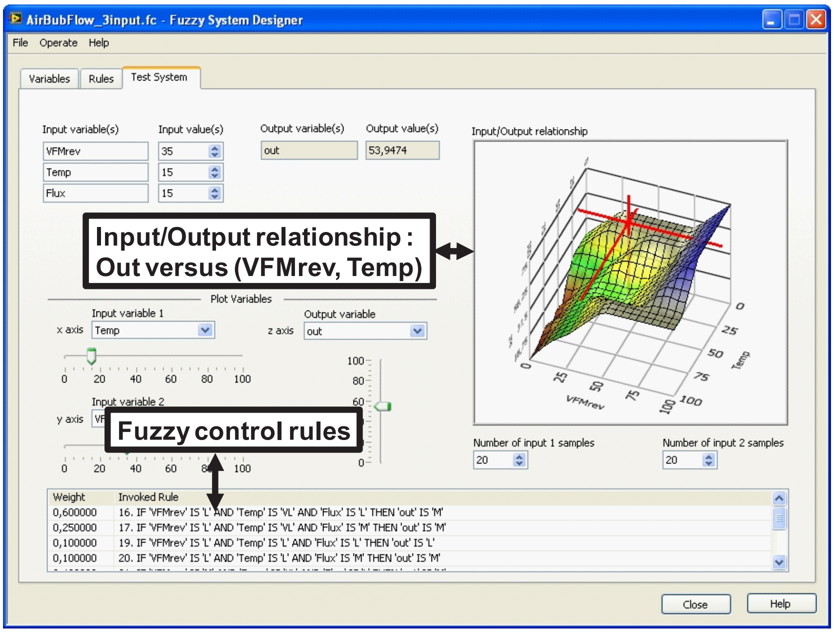

Fig. 7. Fuzzy set rules (lower part) and output response.

rules base of the AirFlow control. A very important aspect of FSL control with respect to the fuzzy rules is the use of linguistic variables. This allows the straightforward writing of control rules, mimicking the reasoning and actions of a human operator.

A fuzzy rule is then typically written symbolically as:

If U = Low AND if V = Low AND if W = High AND if X = Very Low then Y = Medium

It should be noted that fuzzy operators AND, OR, etc. are not related in any way to classic Boolean logical operators since Boolean operators cannot handle conditions which are "more-or-less true". Therefore specific fuzzy operators have been defined mathematically in fuzzy set handling. These definitions are however not the subject of this publication and can be found in the existing literature on FSL (e.g. [4]).

If the linguistic input variables *U*, *V*, *W* and *X* e.g. each consist of 5 fuzzy sets having the linguistic names Very Low, Low, Medium, High and Very High, then it is obvious that it is possible to create $5^4 = 625$ fuzzy rules based on MBR operator expertise. It is however not necessary to define all 625 rules since it is possible to de-activate IF-rule combinations of *U*, *V*, *W* and *X* which are irrelevant or of low importance.

It is not the goal of this publication to go into details with respect to the actual implementation of all the fuzzy rules (also for proprietary reasons). The basic approach being involved is assumed to be clear while specific information on the handling of fuzzy rules can be found in the literature [2–7,14].

During the fuzzy inference handling of the fuzzy rules, there are two major actions: aggregation (the calculation of the IF parts) and composition (the calculation of the THEN parts). These calculations result in the linguistic value of the linguistic output variable. Information on the specific methods as used for aggregation and composition can be found in the literature on FSL (e.g. [4]).

It is possible to implement relevant operator knowledge as fuzzy rules and evaluate first the fuzzy control block response of an output variable by simulation. The fuzzy rules or even the fuzzy membership sets can then be further fine-tuned in order to obtain a proper fuzzy controller response. This tuning can also be enhanced over time while operating the MBR. In the extreme case, it would also be possible to implement neuro-fuzzy methods which would allow the MBR filtration system to become self-learning. In principle, neuro-fuzzy self-learning allows the system to automatically optimize over time, during the operation of the MBR, the fine-tuning of the knowledge (fuzzy rules) or the fuzzy sets.

3. Experimental and first results

Detailed MBR pilot test results over a long test period in 2008–2009, involving a FSL based ACS is presented in [15]. Therefore only first results are discussed here briefly, as obtained at the start of the European FP6 project AMEDEUS (see acknowledgments), while proving here the ACS functionality.

The FSL based ACS, as described in section 2, was implemented on a MBR pilot unit and tested at a municipal waste water treatment plant (WWTP) in Belgium. The pilot unit included pretreatment (screen, grease tank, grit/grease trap and pH correction) and was fed by the waste water arriving at the WWTP. The pretreated waste water was thereafter handled by an anoxic compartment (2 m^3) and an aerobic compartment (4 m^3). The pilot was fully automated (MeFiAS® controlled) and had on-line sensors for oxygen, temperature, pH, level, flow and pressure. The MeFiAS® process data and control parameters were analyzed and tuned through remote control at the VITO premises.

Two 20 m^2 membrane modules (A3 Water Solutions GmbH, Gelsenkirchen, Germany) were submerged in a separate 2 m^3 filtration compartment in a double deck configuration. The aeration of the module was flow controllable. The permeate flux during filtration was adjusted by a flow controlled pump.

The effect of the ACS is indicated here for a single experimental case at the start of the MBR experiments, and for a restricted combination of operational MBR conditions. After a start-up period and gradual increase of the flux to the 15 L/h.m² value, the MBR was operated for about another 4 weeks (without the ACS). A regime of 8 min filtration and 2 min relaxation was applied. During that reference period the coarse bubble aeration flow through the filtration modules was constant at a level of 18 Nm³/h. It can be observed in Fig. 8 that around April 20th 2008 there was an electrical failure which induced a standstill for a few days after which the installation was restarted at a lower flux of 10 L/h.m² for about one week. The flux was then again increased to 15 L/h.m². Some gradual decline of the permeability was noticed during the succeeding operational days of the reference period.

On May 5th, the first ACS test with variable membrane aeration was initiated. The functioning of the ACS was studied during the succeeding period of three weeks by activating two ACS input parameters (MBR–VFM_{rev} and Temperature) in order to have the set-point of the coarse bubble aeration flow within MeFiAS® being supervised by the ACS. The reversible fouling propensity value F_{rev} was determined daily with the MBR–VFM measurement. The crisp F_{rev} value and the mixed liquor temperature value were then used as the ACS input. The fouling propensity of the mixed liquor was found to be low during this initial ACS test period. An alarm however on Friday evening May 9th halted the pilot for another few days after which the testing was continued. In the ACS settings (Fig. 5), the 0–100% normalized interval for the temperature corresponded to the range of 5–40°C while the 0–100% normalized interval for the coarse membrane bubble aeration flow ranged from 10–18 Nm³/h. The ACS determined the corresponding value for the set point of the aeration flow and transferred that value to the "lower level" MeFiAS® control system. As a result of the low fouling propensity, the ACS actually reduced the aeration flow to the low normalized value of 0% (10 Nm³/h). The flux was kept constant at 15 L/hm². It can be noticed from Fig. 8 that the permeability was comparable to the one in the reference period. It was thus concluded from this preliminary first run of the ACS that the ACS software was in principle functional and seemingly allowed for a substantial reduction of the MBR filtration module aeration. This conclusion is also extrapolated in [15] which describes in more detail the broad experimental work on the ACS within the framework of the AMEDEUS FP6 MBR project. As discussed in [16], aeration involves up to 60–70% of the energy consumption. From that perspective

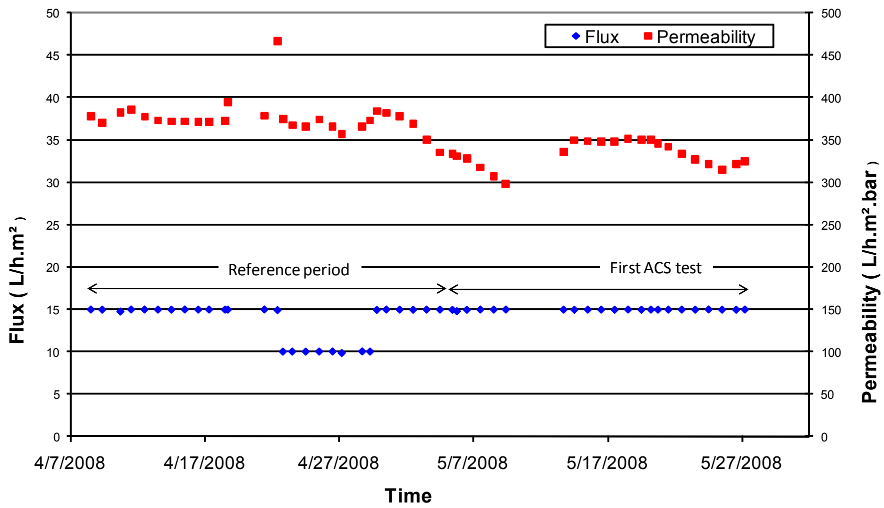

Fig. 8. First ACS results.

and from the results in this publication and those referred to in [15], the energy savings by using the ACS could well be in the substantial range of 20–30%.

There was also a comparable biological performance of the MBR pilot during both periods, as deduced from the COD removal. That removal was thus not negatively influenced by the lower coarse bubble aeration flow in the submerged membrane compartment. Additional fouling indicators such as DOC, sugar/protein concentration and mean particle diameter also did not differ much for both periods.

4. Conclusions

It is illustrated that an advanced MBR control system can be based on FSL. An FSL approach does not need complex mathematical input-output process model equations or complex control algorithms. Even more, the implementation of mathematical models would invoke the need for multiple (expensive) characterization systems, which moreover need high-skilled operators, thereby increasing costs. It is also often the case that a complex process requires a substantial and costly development time of the mathematical model, additionally often being sensitive to a risk of low accuracy. The alternative approach of a FSL control approach typically requires less development time.

As a result of the availability of a Fuzzy Toolbox software module for LabVIEW, a FSL based ACS could be developed. The LabVIEW compatibility significantly enhanced the linking of the "higher level" ACS and the "lower level" MeFiAS pressure driven membrane software control. The ACS software was fully implemented for specific input and output process parameters and tested in a MBR pilot on location of a WWTP. The first results from MBR pilot tests showed that the ACS concept was fully feasible.

It should also be remarked that the ACS, based on FSL, and the VFM is not restricted to the control of the filtration process within MBR's but could also be used in the control of classic pressure driven membrane filtration (MF, UF, NF) processes.

Acknowledgments

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